Prescription Drugs, Medical Care, and Health Outcomes: A Model of Elderly Health Dynamics

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Abstract

A Medicare prescription drug benefit is one of the most important health policy issues for elderly persons in the U.S. today. Most of the studies addressing this policy issue have focused on the direct cost of a drug benefit if one were provided. However, few previous studies have investigated potential benefits, namely how greater prescription drug use may affect inpatient care or other Medicare-covered services. Cost projections from studies that fail to measure the impact of a drug benefit on utilization of other forms of medical care may over or under estimate the net cost of the policy change. This study uses a dynamic framework to explicitly explain how individual outpatient prescription drug utilization and inpatient care utilization are related over time through a health production function. The theory suggests a set of demand equations and health transitions that are jointly estimated. Longitudinal data from the Medicare Current Beneficiary Survey from 1992 to 1998 are used to quantify the effect of outpatient drug expenditures on health status and subsequent Medicare Part A expenditures of the elderly. Assuming that each Medicare beneficiary is given a prescription drug benefit at a typical Medicaid prescription drug benefit level, our simulation results show that a prescription drug benefit may stimulate demand for outpatient drugs, help decrease mortality and increase the longevity of Medicare beneficiaries. Over a short period, there could be offsets of Medicare Part A expenditures because of increased prescription drug utilization, but over a longer period of up to five years, total Medicare Part A expenditures are more likely to increase because of increased longevity and population size.

1 Introduction

On November 26th, 2003, Congress passed the Medicare Prescription Drug Bill in the greatest expansion of Medicare benefits since its creation in 1965. Despite passage of this landmark legislation, policymakers and researchers still fiercely debate two unanswered questions about the Drug Bill. Will it improve the health of elderly Americans? And what will it cost? Proponents of the Drug Bill argue that higher outpatient prescription drug utilization will improve the health status of Medicare beneficiaries. Opponents are concerned that prescription drugs will have little effect on morbidity and mortality. As for the cost, there is no consensus regarding the appropriate methodology for cost estimation, so not surprisingly cost estimates for the new drug benefit program vary wildly. Legislators who opposed the Drug Bill complained that the original budget projection of $400 billion was too high. Then in February 2004, the White House revised the budget estimates to an even higher limit at $540 billion.

These two debates are closely related. If proponents are correct that increased prescription drug use will improve health status, then short-run expenditures may fall, particularly if inpatient stays are avoided. In the longer run, though, decreased mortality could increase lifetime prescription drug expenditures. Investments in health today affect future health status and expenditures (Grossman, 1972), and it is the relationship among use and morbidity and mortality over time that we explore in this study.

Most of the health economic studies addressing this policy issue have focused on estimating the direct effect of Medicare drug insurance on demand for prescription drugs. This results in a static cost estimate of the drug benefit. However, long-run Medicare costs could change not only from the moral hazard effects of having drug coverage, but also from changes in morbidity and morality associated with changes in drug (and other medical care) utilization. Few previous studies have investigated the long-term costs and benefits of the drug policy. Increased prescription drug use may improve Medicare beneficiaries' health, lower the disability rate, and decrease mortality (Philipson and Becker, 1998). Improved health and lower disability rates may in turn lead to reduced hospitalization and Part A cost. Decreased mortality, however, increases the total number of Medicare beneficiaries as well as their demand for Medicare-covered services. Cost projections from studies that fail to measure the morbidity and mortality consequences of the increased consumption of drugs may over or under estimate the net financial cost of the policy change.

This topic requires a dynamic behavioral model to explain why an increase in prescription drug utilization induced by more generous insurance could affect the subsequent Medicare Part A and Part B expenditures of the elderly through changes in health status, disability rates, and mortality over time. We use data from the longitudinal Medicare Current Beneficiary Survey Data (MCBS) from 1992 to 1998 to jointly estimate a system of empirical equations representing drug and medical care demand and a health production function. Our results therefore quantify the effect of increased prescription drug use on Medicare beneficiaries' functional status and mortality and their subsequent demand for drugs as well as Medicare Part A and Part B services. We then simulate the immediate (or direct) effect of a change in drug coverage, and the long-run (5 years) effect that incorporates previous responses to the policy change. We show that for every dollar spent on prescription drugs, Medicare will only save a few cents in cost offsets. In addition, the health status from increased prescription drug use will improve slightly over time.

This paper fills a large void in the policy debate about the Medicare prescription drug benefit, as well as in the health economics literature, by investigating the dynamic nature of elderly health care behavior and simulating both the immediate and long term policy effect of a prescription drug benefit on the health outcomes of the elderly and the total cost to Medicare. Dynamic behavioral models are appropriate when studying complex behavior over time. Our dynamic model guides our choice of empirical model. Fortunately, our longitudinal data are sufficiently rich in both health and expenditure information to estimate the dynamic empirical model. We use the results from estimation of the model to answer the policy questions, not only for the sample as a whole, but also for interesting subpopulations defined, for example, by specific health conditions.

2 Background and Literature Review

Even without Medicare prescription drug coverage, elderly Americans spend a large amount on outpatient prescription drugs. In 1995, approximately 85 percent of the noninstitutionalized elderly had at least one prescription, and the average annual outpatient prescription drug expenditure was around \$600 per person and \$22 billion in total (Poisal et al., 1999). Although the elderly only account for 12.4% of the total population, their drug expenditures account for one-third of the total drug expenditures of the entire population (DHHS, 1998; Long, 1994). Elderly persons have greater demand for prescription drugs because of worse general health, higher disability rates, and a higher prevalence of chronic diseases (Adams et al., 2001a; Blustein, 2000; Johnson et al., 1997; Lillard et al., 1999; Poisal et al., 1999; Rogowski et al., 1997; Soumerai and Ross-Degnan, 1999; Stuart and Coulson, 1994).

Despite the high demand, insurance coverage of outpatient prescription drugs is limited among the elderly. The current Medicare program does not cover most outpatient prescription drugs. About 65% of Medicare beneficiaries have some drug coverage from at least one supplemental insurance plan, leaving 35% who pay for all their outpatient prescription drugs out of pocket. Among those with drug coverage (which may be from multiple sources), about 44% have employer-provided insurance, 16% have privately-purchased insurance, 16% have Medigap insurance, 11% have Medicare HMO, 17% have Medicaid, and 4% have other publicly-provided coverage, including Veteran Assistance or state Pharmacy Assistance (Poisal et al., 1999). Adverse selection suggests, however, that those who purchase additional insurance beyond Medicare are those who expect to have higher than average expenditures.

Although more than half of the Medicare enrollees have at least one type of drug coverage, the current drug insurance plans are not comprehensive enough to ensure adequate outpatient prescription drug utilization among senior citizens. Out-of-pocket payment is still the largest source of outpatient drug payment for the elderly people, and accounts for 50% of total drug expenditures. Previous research shows that lack of sufficient insurance coverage is one major reason for under use of prescription drugs, especially clinically-essential drugs. Steinman and colleagues found that, among elderly people age 70 and older in the U.S., chronically ill patients without drug insurance were more likely to restrict their medication by skipping doses or to avoid using medication than those with drug insurance (Poisal et al., 1999; Steinman et al., 2001). Federman and colleagues found that, among Medicare beneficiaries with coronary heart disease, those without drug insurance have disproportionately higher out-of-pocket prescription drugs expenditures, but a lower use rate of statin, which is a class of expensive and effective cardiovascular drugs (Federman et al., 2001). With the development of newer and more effective drugs and the rapidly increasing price of those drugs, lack of sufficient drug insurance may worsen the occurrence of under utilization of prescription drugs among the elderly people. Poisal and Murray (2001) found that elderly Medicare beneficiaries with drug coverage received 9% more prescriptions on average over one year, while those without any drug coverage received 2.4% less prescriptions. Even among those Medicare beneficiaries who have drug insurance, high copayment rates or other cost-sharing limitations may also restrict the appropriate use of clinically-essential prescription drugs (Reeder and Nelson, 1985; Soumerai et al., 1987; Soumerai et al., 1994; Soumerai and Ross-Degnan, 1990; Soumerai et al., 1991). For these reasons, some Medicare beneficiaries may eventually require Part A services that could have been avoided had their diseases been controlled with sufficient prescription drugs utilization.

Most of the existing studies that investigate the potential costs of a Medicare prescription drug benefit are cross-sectional and focus on estimating the immediate effect of insurance coverage on drug utilization. Generally, these studies provide strong evidence that insurance coverage has a positive effect on prescription drug use. Studies using nationwide data found that drug insurance, including both private and public insurance, is positively associated with utilization of outpatient drugs, and the more generous plans have the strongest positive effects (Adams et al., 2001b; Blustein, 2000; Lillard et al., 1999; Long, 1994; Poisal et al., 1999; Rogowski et al., 1997). Other cross-sectional studies conducted at the state or community level draw similar conclusions (Fillenbaum et al., 1993; Stuart and Coulson, 1993; Stuart and Grana, 1995).

Few previous studies have investigated the consequences of drug insurance and prescription drug use on health outcomes and other health care costs. A few well-controlled longitudinal studies suggest that limited access to drugs could lead to worse health and higher hospital care utilization. Soumerai and his colleagues found that reduction in utilization of outpatient drugs (manifested in under use of clinically-essential drugs) associated with a prescription limitation cap in New Hampshire led to increased hospital and nursing home admission rates among elderly beneficiaries (Blustein, 2000; Soumerai et al., 1991). For mentally ill patients, the increase in the cost of non-drug medical services even exceeded the savings in reduced prescription drug use (Soumerai et al., 1994). A study conducted in Canada revealed that greater consumer cost-sharing for prescription drugs led to a reduction in consumption of essential drugs, and higher rates of adverse health events and emergency room visits among elderly persons (Tamblyn et al., 2001). These studies provide valuable evidence that more complete insurance coverage of prescription drugs could encourage more appropriate drug use and reduce other non-drug health care costs, and therefore they support the validity of the argument of offsets in non-drug expenditures from increased prescription drug use. However, none of this research was conducted on a representative sample of Medicare beneficiaries, nor did the research quantify the long-run effect of drug use on health outcomes and other non-drug health care costs.

Lichtenberg (2001) quantified the short-run relationship between prescription drugs and other health care utilization using data from the Medical Expenditure Panel Survey (MEPS). He found that higher utilization of newer and more effective drugs could reduce non-drug health care expenditures including inpatient care. In particular, the reduction in hospital costs associated with more drug use could be as much as 300% according to his research. Although MEPS is representative of the entire U.S. population including both working individuals and the elderly, we speculate that the impact of drug use on inpatient care costs in Lichtenberg's study is over estimated for two reasons. First, that study is a cross-sectional study that estimates the effects of drug use on current inpatient care instead of subsequent inpatient care cost. Theoretically, at the cross-sectional level, the demand for medical care is primarily determined by patients' health status, with healthier patients demanding less hospital care but more outpatient drugs than sicker patients who are hospitalized. Second, the use of drugs and hospital care at a cross-sectional level are simultaneous and endogenous, such that unobserved individual heterogeneity (e.g., unobserved health status, preferences and habit) may influence the demand for both types of health care. Lichtenberg did not address the endogeneity issue with econometric tools, and hence produces biased estimates. The estimated negative cross-sectional correlation in Lichtenberg's study between drug use and hospital care expenditures can hardly be interpreted as an offset in hospital care costs due to greater drug use.

In addition, with regard to the effect of drug use on health outcomes, a few studies provide evidence that higher utilization of clinically-essential drugs or newer drugs may help to decrease the population mortality rate (Federman et al., 2001; Lichtenberg, 2003). Cutler and other researchers cite chronic diseases as the main contributors to functional disability among the elderly, and argue that the development of new drugs and a higher rate of prescription drug use could help to decrease disability rates according to clinical theory, but there is no empirical evidence to support this argument specifically (Cutler, 2001; Ferrucci and Guralnik, 1997). Studies that do not consider the effects of drug use on mortality rates may under estimate the net cost of a Medicare drug benefit because a lower mortality rate and greater longevity may lead to an increase in the total number of Medicare beneficiaries as well as total demand for inpatient care. However, studies that do not consider the possible reduction in disability rates associated with drug use may over estimate the net cost of the drug benefit given the positively correlation between disability and inpatient care expenditures among the elderly (Stearns et al., 2003). If the elderly are able to live longer, but healthier, lives, then the total medical care cost at the population level may not necessarily increase. There is a large void in the existing literature, and a striking omission of longitudinal analyses, that could explain the causal relationship between drug utilization, changes in health status and subsequent expenditures on other health care services among the elderly population (Adams et al., 2001a). This paper answers the call.

3 Model of Dynamic Behavior

3.1 Theoretical Framework

In an effort to understand medical care consumption behavior of elderly Medicare beneficiaries over time, we model annual utilization and associated health transitions from age 65 to a maximum potential age T^*, and T is the observed age of death for decedents in the data ($T \leq T^*$). We make use of recursive Bellman equations to model the dynamic behavior over time. Applications of this approach to medical care use and health behavior include Gilleskie (1998), Gilleskie and Mroz (1998), Khwaja (2003), and Crawford and Shum (2003). In each year H_t represents health status at the beginning of period t. For simplicity, let $H_t = 0$ if health status is good, $H_t = 1$ if health status is bad, and $H_t = 2$ if the individual dies.

[1] Given her observed health status, an individual optimally chooses a level of outpatient prescription drug utilization, R_t, and utilization of other forms of medical care, M_t. Current health and medical care inputs determine period-by-period health transitions. A health shock, S_t, during period t may also affect health capital production at the end of the time period. The probability of health status H_{t+1} in period $t+1$ is

$$\pi_{t+1}^{h} = \Pr(H_{t+1} = h) = f(H_t, R_t, M_t, S_t), \qquad h = 0, 1, 2, \qquad H_t \neq 2. \tag{1}$$

The functional form $f(\cdot)$ defines the distribution of the random error in empirical estimation (defined in detail later). Let ϕ_t^s be the probability of having a health shock, and let there be s types of health shocks, such that $\phi_t^s = \Pr(S_t = s)$. (In the empirical model we treat these per-period health shocks as exogenous. Future work will relax this assumption.)

The per-period utility associated with each level of current period medical care expenditure (R_t and M_t) depends on current health status, health shocks, health care utilization, consumption, relevant lagged information, and a random error u_t , and is denoted $U(H_t, S_t, R_t, M_t, C_t, R_{t-1}, M_{t-1}, u_t)$, where C_t is consumption of all other goods at time t and is defined by the budget constraint below. Previous health care utilization may directly affect the marginal utility of current alternatives. For example, Medicare beneficiaries with chronic illnesses and a high demand for prescription drugs may develop a habit of, or even addiction to, prescription drugs that is reflected in preferences. As another example, some Medicare beneficiaries may develop a stable and trustworthy relationship with their outpatient care physician over time. An individual with more physician contact (or a regular source of care), all else equal, may be more likely to fill prescriptions and use other forms of medical care in the future because of the relationship that has been established between patient and provider.

During each period t an elderly person spends all of her disposable income on consumption and medical care. [2] Disposable income constitutes income from earnings and benefits, Y_t, net of premiums paid for supplemental health insurance, I_t. All elderly persons

[1]We define the health status in three categories for simplicity of the model. In the empirical model we use more informative measures of health status defined by functional limitations.

[2]Although savings decisions have important implications for health care behavior, and vice versa, we do not consider saving behavior for two reasons. First, there is no saving information in the data. Second, consideration of dynamic saving behavior unnecessarily complicates estimation of the empirical model and could misplace the focus of the study.

(age 65 and older) are eligible for Medicare reimbursement (with nearly all electing both Part A and Part B Medicare coverage). We categorize additional health insurance coverage as either coverage from a Medicare managed care plan, an employer-provided plan, a privately-purchased plan, or Medicaid. The price of the supplemental insurance plan (i.e., the premium) is denoted $q(I_t)$. In estimation of our model, we consider the behavior of those respondents who did not switch insurance plans over time and, hence, treat the observed health insurance coverage of an individual as an endogenous initial condition. Total out-of-pocket expenditures on health care in t, O_t, depend on medical care utilization, the insurance plan, and the price of care, p_t, such that $O_t = (R_t, M_t, I_t, p_t)$. Consumption is defined by the budget constraint in each time period and equals earnings and benefits less premia for insurance and out-of-pockets payments (i.e., $C_t = Y_t - q(I_t) - O_t(R_t, M_t, I_t, p_t)$).

Medicare beneficiaries choose the optimal amount of outpatient prescription drugs and other medical care in each time period to maximize their lifetime utility, which is the sum of current utility and the expected discounted present value of future utility. Future utility depends on stochastic health, health shocks, and uncertain future medical care utilization. The lifetime value at period t of drug expenditure r and other medical care expenditure m conditional on health status h and health shock s is

$$\begin{aligned} V_{rm}^{hs}(Z_t, X_t, u_t) &= U(H_t = h, S_t = s, R_t = r, M_t = m, C_t, R_{t-1}, M_{t-1}, X_t, u_t) \\ &\quad + \beta \left[\sum_{h'=0}^{2} \pi_{t+1}^{h'} \sum_{s'} \phi_{t+1}^{s'} V^{h's'}(Z_{t+1}, X_{t+1}) \right], \ \forall t \end{aligned} \tag{2}$$

where β is the discount factor. The vector $Z_t = [H_t, S_t, R_{t-1}, M_{t-1}, I_t]$ represents the endogenous information available to a Medicare beneficiary prior to making the period t decision, X_t is the vector of known exogenous information, and the maximized expected value of future utility is $V^{hs}(Z_{t+1}, X_{t+1}) = \mathrm{E}_t \left[\max_{rm} V_{rm}^{hs}(Z_{t+1}, X_{t+1}, \varepsilon_{t+1}) \right]$. The value of death is normalized to zero (i.e., $V^2(Z_{t+1}, X_{t+1}) = 0$). The optimal choice of outpatient drug use and other medical care use in period t is that combination that maximizes the value of an individual's lifetime utility.

This theoretical framework explains how outpatient prescription drug utilization and other medical care utilization are related over time. The model illustrates several important dynamic considerations. In particular, current consumption influences future health which will, in turn, determine future consumption. Also, past consumption influences current consumption potentially through pathways other than health. It remains to test these implications empirically.

3.2 Empirical Implementation

The model described above is not parameterized (i.e., specific functional forms of utility, health production, and expectations are not provided) and therefore not estimated. Yet the value functions that describe optimal consumption decisions can be approximated by a Taylor series expansion. Hence, dynamic demand equations for prescription drug use and other medical care services can be estimated jointly with the dynamic health transitions. The empirical objective is to quantify the effect of endogenous and interrelated health care choices on future health. A second objective is to determine the effect of endogenous previous utilization of prescription drugs on current utilization of drugs and other Medicare-covered services.

Corresponding to the theoretical model, R_t measures outpatient prescription drug expenditures in the empirical approximation, and we decompose other medical care, M_t, into Medicare Part A expenditures, A_t, and Medicare Part B expenditures, B_t, (i.e., $M_t = A_t + B_t$). The value of the current optimal choice of outpatient prescription drugs r, Medicare Part A services a and Medicare Part B services b is a linear function of the endogenous variables Z_t, exogenous characteristics X_t and an error term u_t. That is, the value of choosing levels of services a, b, and r at time t is

$$V_t^{abr} = \alpha_0 + \alpha_1 Z_t + \alpha_2 X_t + u_t, \quad \forall t \ . \tag{3}$$

As an approximation of the theoretical model, this empirical model is dynamic because it allows for an effect of endogenous previous health care utilization on current health care choices.

In addition to the observed heterogeneity that may influence the simultaneous demand for Medicare Part A and Part B services and outpatient prescription drugs, unobserved differences in individuals may affect their choices. Our empirical framework attempts to incorporate two types of such unobserved heterogeneity. One type is permanent individual heterogeneity, such as unobserved attitudes toward medical treatment or quality of health care providers. For example, a patient who prefers outpatient care to inpatient care is more likely to choose supplemental insurance with better outpatient physician services and prescription drug coverage and is likely to use more drugs than a patient who better tolerates inpatient care.

The other type of unobserved heterogeneity is time-varying heterogeneity. The time unit of analysis in this study is a calendar year. Within this time frame the health status of Medicare beneficiaries may change significantly. Although the health production function helps to explain health transitions over a year, other unobserved factors also influence changes in health status. An example of an unobserved characteristic that varies over time for a particular individual is the unobserved rate of natural deterioration of health. Although medical care consumption may help people maintain good health, the health status of elderly people deteriorates naturally because of aging. At some point, it becomes difficult to empirically associate greater utilization with improved health outcomes, yet these individuals are observed to continue seeking care. Unobserved time-varying heterogeneity is likely correlated with observed expenditures and health transitions. Without controlling for this kind of time-varying heterogeneity, the estimates of the effect of health care inputs on health outcomes in the health production function could be biased.

In order to control for unobserved individual heterogeneity, we decompose the error term, u_t, into three components. The first part, μ, captures permanent, or time-consistent, unobserved individual heterogeneity; the second part, ν_t, controls for time-varying unobserved individual heterogeneity; and the third part, ε_t, is a serially uncorrelated and alternative independent error term. Let ρ be the factor loading on the effect of μ, and ω be the factor loading on the effect of ν_t. The error decomposition is

$$u_t = \rho\mu + \omega\nu_t + \varepsilon_t \tag{4}$$

where μ and ν are estimated parameters in the empirical model. One could think of $\rho\mu$ as an individual fixed effect and $\omega\nu_t$ as a time-varying individual fixed effect; the notation chosen, however, is specific to the estimation strategy used to model (and estimate) these two types of heterogeneity. We return to this discussion below.

The distributions of prescription drugs and Medicare Part A expenditures are highly skewed, with many people having zero expenditures. Therefore, current expenditures of these two types of medical care are modelled in two parts. The first part employs a logit model to estimate the probability of any expenditures (Equation 5). That is,

$$\Pr(d_t > 0) = \frac{\exp^{\alpha X_t}}{1 + \exp^{\alpha X_t}} \tag{5}$$

$$\begin{aligned}
\text{where } \alpha X_t &= \alpha_{d0} + \alpha_{d1} X_t + \alpha_{d2} I_t + \alpha_{d3} H_t + \alpha_{d4} S_t \\
&\quad + \lambda_d \left[\alpha_{d5} \mathbf{1}(A_{t-1} > 0) + \alpha_{d6}(\mathbf{1}(A_{t-1} > 0) \cdot Q_{t-1}) + \alpha_{d7} R_{t-1}\right] \\
&\quad + \rho_d \mu + \omega_d \nu_t \\
&\quad (d = (A, R); \quad \lambda = 1 \text{ if } d = R; \quad \lambda = 0 \text{ if } d = A) \\
\text{and } \varepsilon_t^d &\sim \text{i.i.d. extreme value.}
\end{aligned}$$

The second part uses an OLS model to estimate the level of expenditures conditional on positive expenditures (Equation 6). Because almost every Medicare beneficiary uses some Part B services each year, total Part B expenditures are estimated with one OLS equation (Equation 6). Thus,

$$\begin{aligned}
e_t &= \delta_{e0} + \delta_{e1} X_t + \delta_{e2} I_t + \delta_{e3} H_t + \delta_{e4} S_t + \\
&\quad \lambda_d \left[\delta_{e5} \mathbf{1}(A_{t-1} > 0) + \delta_{e6}(\mathbf{1}(A_{t-1} > 0) \cdot Q_{t-1}) + \delta_{e7} R_{t-1}\right] \\
&\quad + \rho_e \mu + \omega_e \nu_t + \varepsilon_t^e \\
&\quad (e = B; \quad e = (A, R) \text{ if } e_t > 0; \quad \lambda = 1 \text{ if } e = R; \quad \lambda = 0 \text{ if } e \neq R).
\end{aligned} \tag{6}$$

The $\mathbf{1}(\cdot)$ function above takes on the value one when the endogenous previous behavior in parenthesis is true and zero otherwise. Q_{t-1} is an indicator of the quarter of hospitalization (if any) in the previous year. The vectors of estimated parameters are α and δ.

Since health transitions are also likely to be a function of the unobserved heterogeneity, the health production function is estimated jointly with the health expenditure equations. This equation is also dynamic because of its dependence on lagged values of health and endogenous inputs. Health is measured as a 6-category outcome representing worsening health, with death as the extreme negative health outcome. Using a multinomial logit model (Equation 8), the health production function is

$$\Pr(H_t = h) = \frac{\exp^{\gamma_h X_{t-1}}}{\sum_{h'=1}^{6} \exp^{\gamma'_h X_{t-1}}} \tag{7}$$

$$\begin{aligned}
\text{where } \gamma_h X_{t-1} &= \gamma_{h0} + \gamma_{h1} H_{t-1} + \gamma_{h2} S_{t-1} + \gamma_{h3} X_{t-1} \\
&\quad + \gamma_{h4} A_{t-1} + \gamma_{h5} B_{t-1} + \gamma_{h6} R_{t-1} + \gamma_{h7} R_{t-1}^2 \\
&\quad + \gamma_{h8}(R_{t-1} \cdot H_{t-1}) + \gamma_{h9}(R_{t-1}^2 \cdot H_{t-1}) \\
&\quad + \gamma_{h10}(R_{t-1} \cdot X_{t-1}) + \gamma_{h11}(R_{t-1}^2 \cdot X_{t-1}) \\
&\quad + \gamma_{h12}(A_{t-1} \cdot H_{t-1}) + \gamma_{h13}(B_{t-1} \cdot H_{t-1}) \\
&\quad + \gamma_{h14}(A_{t-1} \cdot X_{t-1}) + \gamma_{h15}(B_{t-1} \cdot X_{t-1}) \\
&\quad + \rho_h \mu + \omega_h \nu_t \\
\text{and } \epsilon_t^h &\sim \text{i.i.d. extreme value.}
\end{aligned}$$

The vector of parameters, γ, is estimated jointly with the parameters in equations 5 and 6 and the unobserved heterogeneity parameters ($\rho, \mu, \omega,$ and ν).

These six equations (representing medical care demand and health production), along with reduced form equations for initially observed health status, expenditures, and insurance coverage, are estimated jointly and are correlated through permanent unobserved heterogeneity μ and time-varying unobserved heterogeneity ν_t. We treat both error terms as discrete random effects and integrate them out of the model. (See Heckman and Singer (1983) and Mroz (1999) for analyses comparing this procedure and others, and see Goldman (1998), Gilleskie and Harrison (1998), and Blau and Gilleskie (2001) for health economics applications of this method.) Different from the fixed effect or the general random effect approach, the discrete random effect approach assumes error terms in the simultaneous equations have discrete distributions of several mass points of support μ_k and an accompanying probability weight θ_k , $k = 1, \ldots, K$, where K is determined empirically. Analogously, the points of support of the time-varying heterogeneity, ν_{wt}, and the probability weights, ω_w , $w = 1, \ldots, W$, are estimated with the appropriate normalizations for identification. This approach efficiently models the common heterogeneity that affects health expenditures, health outcomes, and initial conditions. The approach is more efficient than a fixed effect approach that requires estimation of $N-1$ additional parameters, where N is the total number of individuals in the sample. Additionally, there is no distributional assumption made about the error terms and, hence, the method minimizes possible estimation bias from the stronger assumption of a specific error term distribution, such as a joint normal distributional assumption imposed in many models of joint behavior (Mroz, 1999). The likelihood function is

$$
\begin{aligned}
L \;=\; & \prod_{n=1}^{N} \left\{ \sum_{m=1}^{M} \theta_m \prod_{j=1}^{4} \Pr(I_1^j = 1|\mu_m)^{I_{n1}^j} \right. \qquad (8) \\
& \prod_{t=2}^{T_n} \left[\sum_{w=1}^{W} \omega_w \Pr(R_{nt} = 0|\mu_m, \nu_{wt})^{1(R_{nt}=0)} \cdot [(1 - \Pr(R_{nt} = 0)|\mu_m, \nu_{wt}) \cdot \phi_r]^{1(R_{nt}>0)} \right. \\
& \qquad \cdot \Pr(A_{nt} = 0|\mu_m, \nu_{wt})^{1(A_{nt}=0)} \cdot [(1 - \Pr(A_{nt} = 0)|\mu_m, \nu_{wt}) \cdot \phi_a]^{1(A_{nt}>0)} \cdot \phi_b \\
& \qquad \left. \left. \cdot \prod_{h=1}^{6} \Pr(H_{nt+1} = h|\mu_m, \nu_{wt+1})^{H_{nt+1}^h} \right] \right\} .
\end{aligned}
$$

Note that this likelihood specification includes the probability of supplemental health insurance coverage in period $t = 1$ as the only estimated initial condition. We actually estimate four additional reduced-form equations in the initial period to capture the probability of any Medicare Part A expenditures and any prescription drug expenditures, as well as the log expenditures on drugs (conditional on any) and the log expenditures on Medicare Part B services. These initial condition equations are necessary because equations in the subsequent period depend on endogenous lagged values. As expected, unobserved permanent individual heterogeneity influences these initial observations.

Identification in this system of equations is straightforward following the arguments of Bhargava and Sargan (1983) and Arellano and Bond (1991). Estimation of dynamic equations with panel data requires exogeneity of some of the explanatory variables conditional on the unobserved individual heterogeneity. Thus, all lagged values of exogenous variables serve to identify the system. Similarly, conditional on the unobserved heterogeneity (μ and ν_t), lagged values of the endogenous variables also aid identification assuming there is no serial correlation in the remaining errors. Additionally, we include some exogenous variables in the reduced-form specification of the initial conditions that do not independently affect the per-period equations. These include height, which serves to measure health during childhood, and many detailed self-reported health conditions. Our specification of the permanent and time-varying unobserved heterogeneity also serves to identify the system, allowing all lagged i.i.d. errors to independently influence current behavior. Finally, the functional forms of the equations are not linear in each circumstance, and hence identification is further enhanced by the non-linear nature of the specification.

4 Data

The Medicare Current Beneficiary Survey (MCBS) provides a unique and rich dataset for estimating the dynamic model detailed above. The MCBS is a longitudinal survey conducted by the Center for Medicare and Medicaid Services. A representative sample of over 10,000 Medicare beneficiaries was surveyed each year since 1992. Each respondent of the sample was surveyed three times a year. At the first interview, the respondents answered questions about their demographics, insurance and health status, including their functional status and chronic conditions. After the first interview, the respondents were asked to keep the receipts of all their medical bills subsequent to the first interview. The bills were then collected to keep track of the use and cost information. At the end of each year, usually between September and December, the respondents answered the survey question about their health status again in order to update changes in their health status. The respondents were also asked to report their insurance status within each calendar year at the monthly level.

Information in the MCBS is recorded at the calendar year level and provided in two major parts — the survey files and the events files. The survey files contain the survey information, including demographics, monthly insurance coverage, and health status. The events files include the date, charge and payment information of each inpatient, outpatient, medical provider, nursing home, home health and hospice event since the first interview. The charge and payment information of each prescription or refill are also recorded, but the exact date of each prescription or refill is not available.

This study uses the MCBS files from 1992 to 1998. The unit of analysis is a person year. In order to focus on elderly Medicare beneficiaries, this study first excluded the respondents under age 65. After this initial exclusion, 25,208 unique individuals remained in the sample. Because the expenditures of outpatient prescription drugs are not available from the MCBS for people who lived in long-term care facilities, we exclude 3,740 people who lived in a nursing home at any time during the survey period. Because few individuals switch, add, or drop supplemental insurance coverage, we exclude those observed to change insurance coverage over time (7% of respondents during our sample period). This allows us to avoid modeling the rare event of changing supplemental insurance coverage, yet we still model the endogeneity of the initially-observed supplemental insurance coverage.

As part of a longitudinal survey, the respondents were followed more than one year in MCBS. This feature of MCBS is important, because it makes it possible to estimate the effect of drug utilization on subsequent hospital utilization in the next year. However, not all of the respondents in the sample were followed for multiple years. Some of them died or dropped out during the survey period. Table 1 shows the sample distribution of the data by number of years followed. Among the 20,013 unique people, 14,472 were surveyed for more than one year. The majority of the respondents were followed for two or three years. About 5 percent of the sample were followed for five years. This final sample of 14,472 people contributes 42,294 person-year observations used to estimate the per-period expenditures and health outcomes. Observations in an individual's first year of the survey define the initial conditions.

We adjusted all the expenditures in the sample to 1998 dollars, using the Consumer Price Index of Medical Services. Figure 1 depicts expenditures on prescription drugs and Medicare Part B services by age. On average, annual Medicare Part B expenditures were $1,638, with evidence of greater expenditures by age. This simple graph illustrates the complexity in understanding medical care use and its association with age and health. That is, those individuals who live longer are likely to be in better health, and hence may consume fewer medical care services. This is evidenced by the apparent reduction in average expenditures at very old ages. The average annual outpatient prescription drug expenditure was $645. Again, it appears that older individuals spend less on these medical care expenses, with utilization rates remaining constant at around 90% across all ages. Figure **??** illustrates similar patterns of inpatient expenditures (conditional on any) with age. However, the probability of any hospitalization increases dramatically with age from around 12% at age 65 to over 30% at ages above 90. The lower average hospital expenses suggest that the stays of older patients may be shorter than those of younger patients.

Measurement of health status should reflect true health as as accurately and broadly as possible. Rather than use subjective self-reported health, we select the somewhat more objective measures of functional status. About 15 percent of the sample respondents have difficulties in Instrumental Activities of Daily Living (IADL), and more than 30 percent of the sample respondents have difficulties in at least one Activity of Daily Living (ADL). The six categorical values of health capital at the beginning of each year, H_t, are constructed from these measures of functional status, indicating whether the respondent has 1) no functional impairment; 2) any IADLs only; 3) 1 or 2 ADLs; 4) 3 or 4 ADLs; 5) 5 or 6 ADLs; or 6) dies in the current year. In the MCBS, the survey of functional status is conducted between September and December in every calendar year. Table 2 details health transitions of the elderly over the sample period. Obviously the transition rates differ by age and other characteristics, yet this table demonstrates the extent of movement among health categories in general. About half of the elderly remain in a given health state from one year to the next. However, transitions to poorer health are likely, and almost 4% of those with no functional limitations die while nearly 20% of those with 5-6 ADLs die over the sample period. Interestingly, the incidence of health improvement is significant. Over 20% of the sample experiences improved health from one year to another.

Table 3 summarizes additional variables used to explain expenditures and health transitions. These include both endogenous variables (which are jointly modeled with the main expenditure and health equations) and exogenous variables. Note that most of these variables vary across time. The sources of major supplemental insurance for Medicare beneficiaries are the Medicare managed care option, Medicaid, employer-provided insurance, and individually-purchased insurance. In order to simplify estimation, we grouped the employer-provided, privately-purchased, and managed care insurance by whether it offered outpatient prescription drug coverage. Thus, in the empirical model, supplemental insurance includes three dummy variables indicating whether the Medicare beneficiary enrolls in Medicaid, any private insurance with a drug benefit, or any private insurance without a drug benefit. (The initial condition equation is a 4-choice multinomial logit with the additional outcome of not supplementing Medicare.) About 13% of the Medicare-covered sample respondents were also Medicaid beneficiaries, and 51% of the sample respondents were enrolled in at least one type of private insurance with a drug benefit. Altogether, almost two-thirds of the sample respondents had at least one type of outpatient prescription drug insurance.

Five diseases or injuries account for most health shocks, including death, among the elderly population. These include: cancer; heart disease; cerebrovascular diseases; pneumonia, COPD and other respiratory system diseases; and hip and other body part fractures. In the empirical model, the health shocks, S_t, are measured by whether respondents were *diagnosed* in period t with any one of these five life threatening diseases or injuries. The survey also includes self-reported chronic conditions present in any period. More than half of the sample respondents have hypertension, 24 percent have had a heart attack, 33 percent have cancer and 17 percent have diabetes. In each year, 6 percent of the surveyed population were diagnosed with cancer, 22 percent were diagnosed with heart diseases, 4 percent were diagnosed with cerebrovascular diseases, 22 percent were diagnosed with respiratory system diseases (including pneumonia with heart/lung co-morbidities, COPD, and influenza), and about 1 percent suffered from hip and other body part fractures.

Table 3 also details demographic information about our sample. As a representative sample of aging Medicare beneficiaries, the average age of the sample is 75.2 years. Sixty percent of the sample are female. One-half of the respondents are married, and 40 percent are widowed. Minority populations account for 12 percent of the entire sample, and 27 percent of the sample are rural residents.

5 Estimation Results

While it is difficult to interpret estimated coefficients on specific variables in the system of equations, it is beneficial to compare the estimates from our jointly estimated system of equations with those produced by estimating each equation separately. The latter method does not account for the correlation across equations and across time, and hence treats previous behavior and health as exogenous. On the other hand, the coefficients from the jointly estimated system reflect unbiased coefficients on the endogenous variables. A brief examination of these differences is warranted. Later, we discuss simulation results from our model which better illustrate the influence of particular variables on outcomes of interest.

Tables 4a through 4c display selected parameter estimates explaining medical care demand. It is interesting to point out that the effect of Part B expenditure in the previous year on the probability of any drug use in the current year switches signs from being positive in the model that does not control for unobserved individual differences to one that models the unobserved heterogeneity (Table 4a). Accounting for the endogeneity of health insurance coverage (i.e., adverse selection) also reduces the effect of coverage on drug use. The effect of Part B expenditures, as well as hospitalization, in the previous year, on drug expenditures is smaller when we model the endogeneity of these previous behaviors.

In Table 4b, we again find that modeling the unobserved correlation between Part B expenditures and inpatient use produces a change in sign, with previous physician service use reducing probabilities of current hospitalization. Drug use in the previous year also reduces subsequent hospitalization. The effects of expenditures in the previous year on Part B expenditures in the current year fall dramatically when we account for unobserved heterogeneity (Table 4c). Similarly, the health insurance effects, while still significant, are smaller. These findings will have significant effects on the long-run cost projections associated with a Medicare drug benefit.

We proposed, above, that the unobserved heterogeneity that influences consumption of different types of medical care might be something like attitudes toward treatment: individuals with a greater mistrust of medicine, all else equal, may consume fewer drugs and have lower other medical care expenses each period. The results from the expenditure equations suggest that these behaviors are endogenous and correlated. We expected the effects of endogenous variables in the health production function to be different from those of a single equation model where expenditures and lagged health are treated as exogenous. To our surprise, the coefficients are quite similar (see Table 5). This suggests that the unobserved heterogeneity captured by our model influences consumption behavior, but is independent of health transitions, conditional on these expenditures. And quite possibly, the unobserved heterogeneity is picking up something orthogonal to health such as difficulty obtaining care that, once controlling for expenditures, has no effect on health transitions. Other empirical work modeling the health production function with panel data has found similar results, despite using a different data set (Bryant, 2003). This finding does not invalidate the methods we use, but simply highlights the difficulty in understanding and appropriately modeling the effect of medical care inputs on health outcomes.

We demonstrate the fit of the model by comparing observed outcomes with model predictions using observed explanatory variables. The top panel of Table 7 summarizes each outcome by year, as observed in the sample. The lower panel reports predictions from our model using the observed data as regressors. While we could show the fit of the model along many different dimensions (e.g., specific expenditures by age and health status), we display here, for brevity, how the model matches very well the unconditional distributions of expenditures and health.

6 Simulation and Discussion

Due to the nonlinearity of the model (both in terms of functional form and specification), implications of the model are best inferred from simulations of the expenditure decisions and health transitions. That is, in each period we use the estimated model to predict demand for prescription drugs and Medicare Part A and B services. We use these simulated input choices and the estimated health production function to update current health. This simulated health outcome is then transferred to the next period, where health shocks are simulated. Conditional on the updated health and health shocks, expenditures are again simulated. This process is repeated for any number of years. We use the simulated values of all endogenous right hand side variables but retain the observed (in the original data) values of exogenous variables (e.g., age, marital status, rural residency, etc.).

This simulation procedure produces long-run effects of policy changes and incorporates the dynamic effect of a policy change on behavior that has consequences for future choices and health transitions. If we did not update the data to reflect these simulated choices, and instead used the model to predict behavior each year and retained the original values of explanatory variables in the following year, then we uncover the immediate effect of any policy change. That is, we would not allow the policy change to have dynamic effects. This simulation would be consistent with results reported from static models that do not capture the effects of altered behavior on future outcomes. Below we discuss our findings from both the short-run simulation (i.e., the immediate effect) and a long-run simulation (i.e., the dynamic updated effect). In each case the policy scenario is one in which prescription drugs are covered by Medicare. This is imposed in the model by assuming that each individual has a Medicaid-like benefit that fully covers prescription drug costs.

The short-term simulation results are quite different from the long-term simulation results(See in Table 7). If we give all the Medicare beneficiaries with a drug benefit as generous as the average Medicaid level, the utilization rate of drugs may increase, and the drug expenditures conditional on using any will increase also. However, because we controlled for unobserved individual heterogeneity, the simulated prescription drugs expenditure using the estimates from the jointly equation system is less than the simulated drug expenditure using estimates from each single expenditure equations, which indicate it is necessary to control for unobserved individual heterogeneity even when estimating the static effect of drug policy, because both the insurance choices and previous health care utilization are highly endogenous with the current drug consumption.

The long-run simulation using both the estimates from the jointly equation system and single equations show that over a long time period up to 5 years, drug policy may help to increase the survival rate of the elderly (with survival rates 0.819 vs 0.798 without controlling heterogeneity, and 0.822 vs 0.803 controlling for heterogeneity). However, the differences between these two models are about the cost of prescription drugs and other Medicare covered services, in the single equation model without controlling for unobserved heterogeneity, the prescription drugs expenditure conditional on having any increases from $827 to $935, with $108 and %12.3 increase. In the jointly estimated model though, the increase is $148, at %21. But the absolute value of drug expenditure is lower in the joint model. More importantly,in the single equation model without heterogeneity, the there is a significant increase of inpatient care expenditures in long run, with probability of hospitalization increases from 0.18 to 0.196 and inpatient care expenditures conditional of any increases from 12,189 to 14,083. But the simulation results using estimates from the joint equations show a much less increase in probability of hospitalization (from 0.178 to 0.187) and a minor decrease in inpatient care expenditures conditional on having any. So is the expenditures of physician services. The jointly equation system with updates predicts a much less increase in Part B expenditures than the single equation model.

Therefore, from the simulation results we conclude that the Medicare prescription drug benefit will increase the demand for prescription drugs, decrease the mortality rate of the elderly population, but increase the average disability rate of the elderly population as more sick people are living longer. Over a short term, there will be an increase in Medicare cost due to the increase in demand for drugs induced by the drug policy. Over a long term though, there is no obvious increase in demand for hospital care, although the disability rate may increase. But we may expect a significant increase in demand for outpatient physician services. Our study results show that it is important to take the dynamic feature and transition of health into consideration when evaluating the cost and health benefit of Medicare prescription drug benefit. In addition, using econometric tools to control for heterogeneity will make significant difference in the estimation and simulation.

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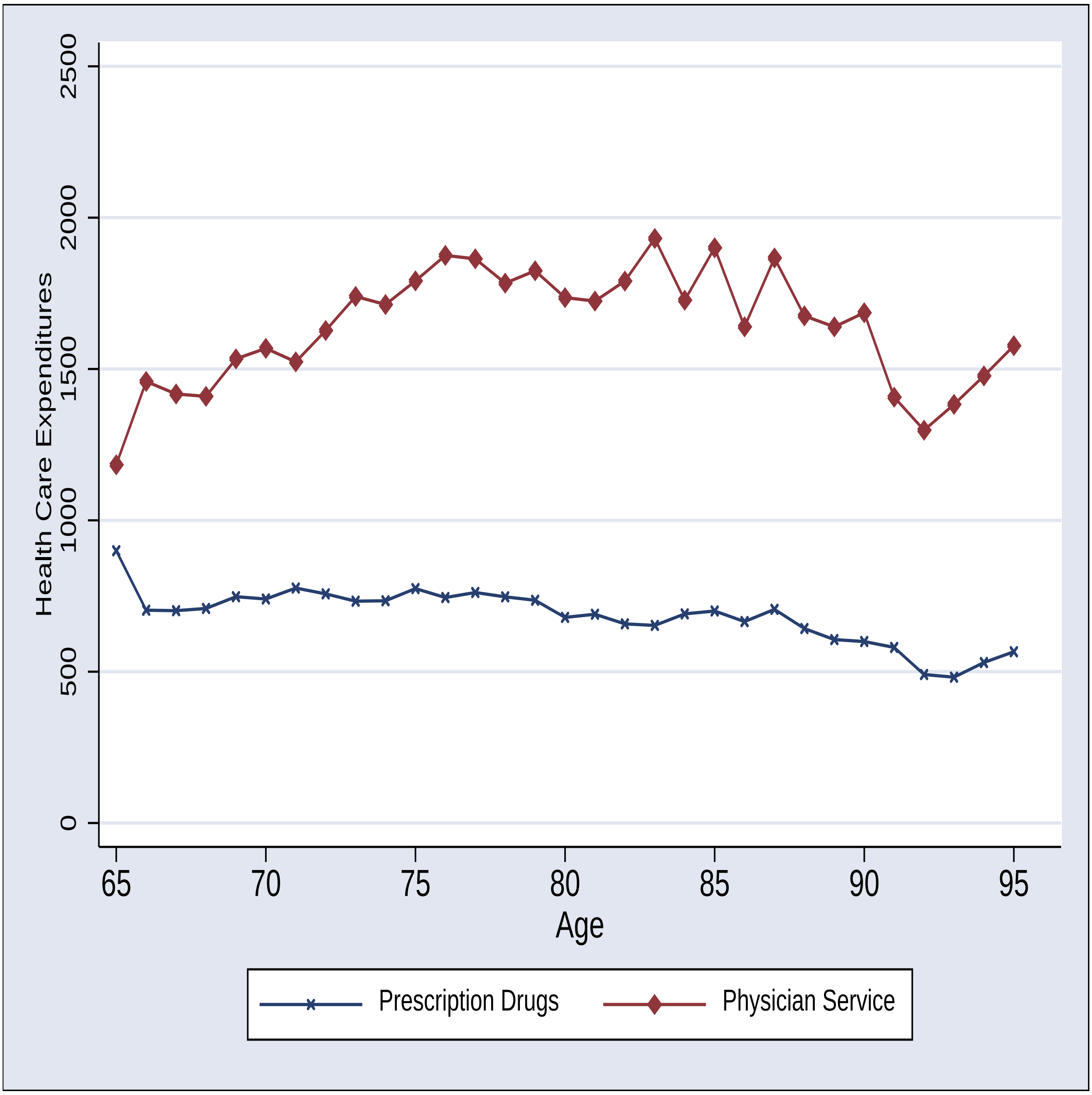

Figure 1: Prescription Drug and Physician Service Expenditures by Age

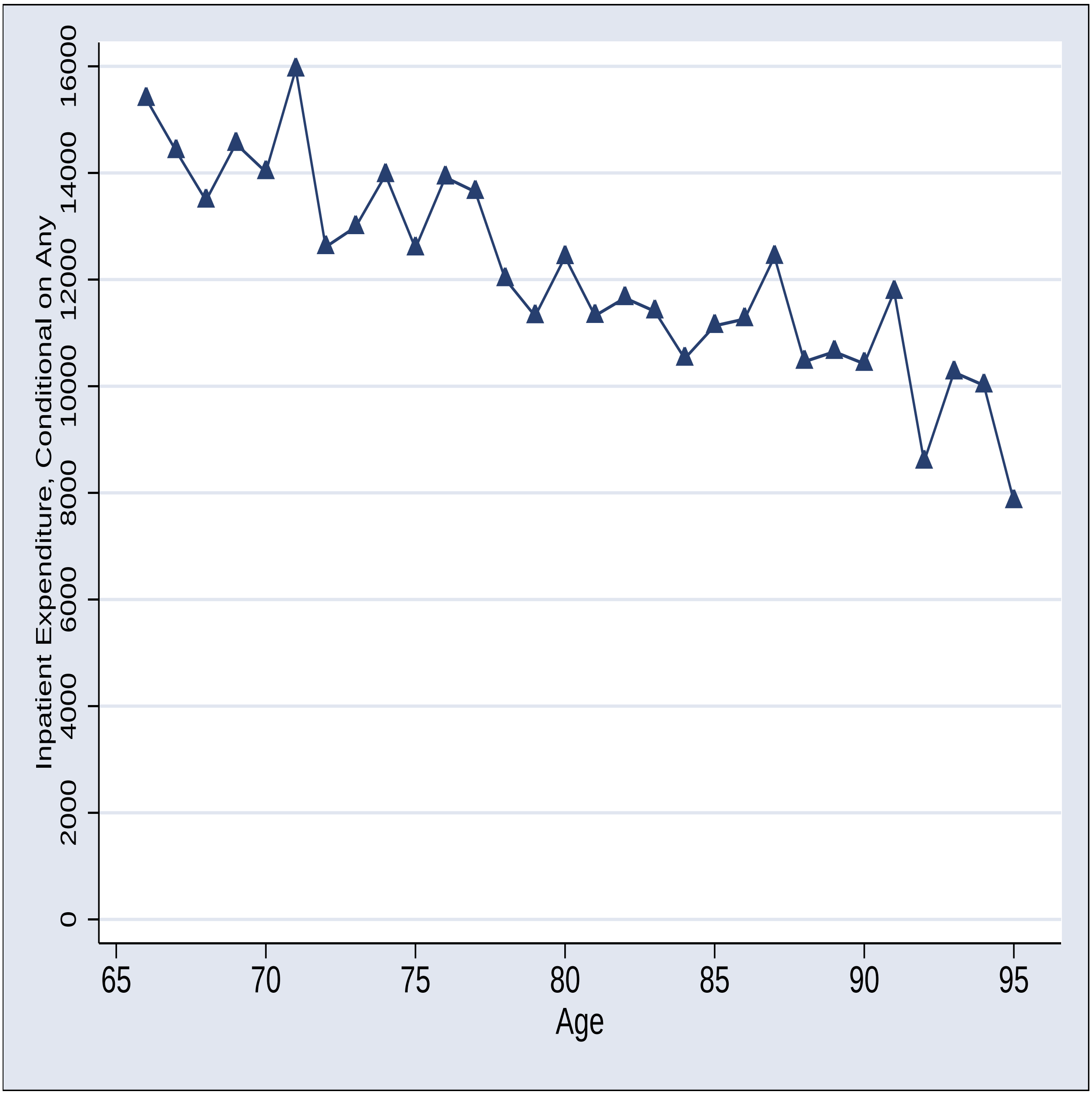

Figure 2: Inpatient Expenditures by Age

Table 1: Empirical Distribution of Participation in MCBS , 1992-1998

Years Followed	# of inds	%	Years Followed	# of inds	%
At Least 1 Year	20013	100	Exactly 1 Year	5541	28
At Least 2 Years	14472	72	Exactly 2 Years	4440	22
At Least 3 Years	10032	55	Exactly 3 Years	7446	37
At Least 4 Years	2586	16	Exactly 4 Years	1854	9
More than 4 Years	732	5	More than 4 Years	732	4

Table 2: Description of Health Status Transitions

	Health Status_t					
	No I/ADLs	IADLs only	1-2 ADLs	3-4 ADLs	5-6 ADLs	Die
Health Status_{t-1}						
No I/ADLs	0.626	0.128	0.155	0.045	0.029	0.039
IADLs only	0.291	0.423	0.231	0.038	0.016	0.050
1-2 ADLs	0.179	0.154	0.509	0.117	0.038	0.066
3-4 ADLs	0.032	0.062	0.296	0.437	0.172	0.095
5-6 ADLs	0.011	0.021	0.082	0.192	0.693	0.195
Die	0.000	0.000	0.000	0.000	0.000	1.000

Table 3: Description of Additional Explanatory Variables

Variable	Mean	Std Dev
Supplemental Insurance		
Medicaid	0.13	0.32
Private Insurance without Drug Benefits	0.27	0.44
Private Insurance with Drug Benefits	0.51	0.50
Health Shocks (Diagnosis in t)		
Cancer (ICD-9 140-209)	0.09	0.23
Heart Diseases (ICD-9 390-430)	0.22	0.41
Cerebrovascular Diseases (ICD-9 430-439)	0.04	0.19
Respiratory System Diseases (ICD-9 480-496)	0.22	0.41
Hip and Other Fracture (ICD-9 820-830)	0.01	0.11
Functional Limitations		
IADLs only	0.13	0.36
1 to 2 ADLs	0.21	0.40
3 to 4 ADLs	0.07	0.25
5 to 6 ADLs	0.05	0.21
Die	0.05	0.21
Self-Reported Chronic Conditions		
Cancer	0.33	0.47
Heart Attack	0.24	0.43
Stroke	0.12	0.32
Diabetes	0.17	0.37
Artery Hardening	0.15	0.36
Hypertension	0.56	0.50
Other Heart Diseases	0.31	0.46
Emphysema, Asthma, COPD	0.14	0.35
Age (range: 65-104 years)	75.21	7.32
Education (range: 0-18 years)	9.83	4.33
Male	0.41	0.49
Rural Resident	0.27	0.45
Race		
Black	0.09	0.29
Asian	0.01	0.07
Other Non-White	0.02	0.15
Marital Status		
Married	0.52	0.50
Widowed	0.38	0.49
Divorced or Separated	0.10	0.30

Table 4a. Selected Parameter Estimates Explaining Outpatient Drug Expenditures

	Logit Model		OLS Model	
	Without Heterogeneity	With Heterogeneity	Without Heterogeneity	With Heterogeneity
Previous Health Care Utilization				
Hospitalized in 4th Quarter of Previous Year	–1.031 **	–1.038 **	–0.044 *	–0.056 **
	(0.129)	(0.134)	(0.024)	(0.025)
Physician Service Expenditure in the Previous Year	0.045 **	–0.035 **	0.011 **	0.003
	(0.009)	(0.010)	(0.002)	(0.002)
Prescription Drugs Expenditure in the Previous Year	0.667 **	0.683 **	0.485 **	0.333 **
	(0.011)	(0.011)	(0.003)	(0.005)
Health Care Utilization in Current Year				
Hospitalized in the 3rd Quarter of Current Year	1.071 **	0.879 **	0.088 **	0.026
	(0.209)	(0.208)	(0.024)	(0.024)
Hospitalized in the 4th Quarter of Current Year	1.249 **	1.031 **	0.147 **	0.079 **
	(0.194)	(0.194)	(0.023)	(0.024)
Supplemental Insurance				
Medicaid	0.298 **	0.189	0.066 **	0.126 **
	(0.110)	(0.115)	(0.027)	(0.029)
Private Insurance without Drug Coverage	0.181 **	0.019	–0.035	–0.025
	(0.090)	(0.095)	(0.024)	(0.026)
Private Insurance with Drug Coverage	0.285 **	0.241 **	0.112 **	0.171 **
	(0.086)	(0.090)	(0.023)	(0.025)
Heterogeneity				
Factor loading on permanent heterogeneity, ρ	—	0.303 **	—	1.768 **
	—	(0.089)	—	(0.042)
Factor loading on time-varying heterogeneity, ω	—	1.502 **	—	0.295 **
	—	(0.067)	—	(0.017)

Note: Standard errors are in parentheses. ** indicates joint significance at the 5% level; * 10% level. Additional explanatory variables include those in Table 3.

Table 4b. Selected Parameter Estimates Explaining Inpatient Care Expenditures (Part A)

	Logit Model				OLS Model			
	Without Heterogeneity		With Heterogeneity		Without Heterogeneity		With Heterogeneity	
Previous Health Care Utilization								
Hospitalized in the Previous Year	0.660	**	0.722	**	0.049		0.079	**
	(0.046)		(0.050)		(0.033)		(0.034)	
Physician Service Expenditure in the Previous Year	0.004		–0.038	**	0.050	**	0.031	**
	(0.009)		(0.010)		(0.007)		(0.007)	
Prescription Drugs Expenditure in the Previous Year	0.023	**	–0.031	**	–0.015	*	–0.032	**
	(0.011)		(0.012)		(0.008)		(0.009)	
Supplemental Insurance								
Medicaid	0.105		0.089		–0.016		0.001	
	(0.083)		(0.087)		(0.065)		(0.063)	
Private Insurance without Drug Coverage	0.176	**	0.136		0.020		0.037	
	(0.077)		(0.081)		(0.061)		(0.059)	
Private Insurance with Drug Coverage	0.174	**	0.184	**	–0.063		–0.011	
	(0.074)		(0.079)		(0.060)		(0.058)	
Heterogeneity								
Factor loading on permanent heterogeneity, ρ	—		0.631	**	—		0.345	**
	—		(0.089)		—		(0.056)	
Factor loading on time-varying heterogeneity, ω	—		1.408	**	—		0.875	**
	—		(0.082)		—		(0.096)	

Note: Standard errors are in parentheses. ** indicates joint significance at the 5% level; * 10% level. Additional explanatory variables include those in Table 3.

Table 4c. Selected Parameter Estimates Explaining Physician Service Expenditures (Part B)

	Logit Model		OLS Model			
	Without Heterogeneity	With Heterogeneity	Without Heterogeneity		With Heterogeneity	
Previous Health Care Utilization						
Hospitalized in the Previous Year	—	—	–0.396	**	0.001	
	—	—	(0.034)		(0.022)	
Physician Service Expenditure in the Previous Year	—	—	0.449	**	0.192	**
	—	—	(0.005)		(0.004)	
Prescription Drugs Expenditure in the Previous Year	—	—	0.107	**	–0.020	**
	—	—	(0.006)		(0.005)	
Supplemental Insurance					.	
Medicaid	—	—	0.490	**	0.185	**
	—	—	(0.054)		(0.038)	
Private Insurance without Drug Coverage	—	—	0.473	**	0.098	**
	—	—	(0.048)		(0.035)	
Private Insurance with Drug Coverage	—	—	0.162	**	0.033	**
	—	—	(0.046)		(0.033)	
Heterogeneity					.	
Factor loading on permanent heterogeneity, ρ	—	—	—		0.547	**
	—	—	—		(0.034)	
Factor loading on time-varying heterogeneity, ω	—	—	—		4.965	**
	—	—	—		(0.024)	

Note: Standard errors are in parentheses. ** indicates joint significance at the 5% level; * 10% level.
Additional explanatory variables include those in Table 3.

Table 5. Selected Parameter Estimates Explaining Health Status Transitions
(relative to the outcome no functional status limitations)

Outcome: IADLs only	Without Heterogeneity		With Heterogeneity	
Health Care Utilization				
Inpatient Care Expenditure	0.064	**	0.060	**
	(0.012)		(0.013)	
Physician Service Expenditure	0.017		0.056	**
	(0.016)		(0.020)	
Prescription Drugs Expenditure	–0.078	**	–0.074	*
	(0.035)		(0.036)	
Square of Prescription Drugs Expenditure	0.024	**	0.024	**
	(0.004)		(0.005)	
Health Status at the Beginning				
IADLs only	2.432	**	2.428	**
	(0.152)		(0.156)	
1-2 ADLs	1.697	**	1.693	**
	(0.187)		(0.189)	
3-4 ADLs	3.478	**	3.556	**
	(0.659)		(0.614)	
5-6 ADLs	2.407	**	2.435	**
	(1.157)		(0.937)	
Interaction of Health Status and Utilization				
IADLs only × Inpatient Expenditure	–0.011		–0.011	
	(0.160)		(0.016)	
1-2 ADLs × Inpatient Expenditure	–0.015		–0.014	
	(0.016)		(0.017)	
3-4 ADLs × Inpatient Expenditure	0.009		0.011	
	(0.047)		(0.043)	
5-6 ADLs × Inpatient Expenditure	–0.173		–0.173	
	(0.102)		(0.099)	
IADLs only × Physician Service Expenditure	–0.039	*	–0.039	
	(0.021)		(0.022)	
1-2 ADLs × Physician Service Expenditure	–0.039		-0.040	
	(0.025)		(0.025)	
3-4 ADLs × Physician Service Expenditure	–0.229	**	–0.246	**
	(0.086)		(0.089)	
5-6 ADLs × Physician Service Expenditure	–0.011		–0.011	
	(0.155)		(0.154)	
IADLs only × Prescription Drugs Expenditure	–0.0209		–0.020	**
	(0.026)		(0.026)	
1-2 ADLs × Prescription Drugs Expenditure	0.029		0.030	
	(0.031)		(0.031)	
3-4 ADLs × Prescription Drugs Expenditure	0.047		0.049	
	(0.102)		(0.098)	
5-6 ADLs × Prescription Drugs Expenditure	0.055		0.049	
	(0.194)		(0.183)	
Factor loading on permanent heterogeneity, ρ	—		–0.070	
	—		(0.087)	
Factor loading on time-varying heterogeneity, ω	—		–0.289	
	—		(0.089)	

Note: Standard errors are in parentheses.
** indicates joint significance at the 5% level; * 10% level.
Additional explanatory variables include individual demographic information.

Table 5. — Continued

Outcome: 1-2 ADLs	Without Heterogeneity		With Heterogeneity	
Health Care Utilization				
Inpatient Care Expenditure	0.063	**	0.060	**
	(0.012)		(0.013)	
Physician Service Expenditure	0.052	**	0.082	**
	(0.017)		(0.022)	
Prescription Drugs Expenditure	–0.057		-0.057	**
	(0.037)		(0.038)	
Square of Prescription Drugs Expenditure	0.026	**	0.027	**
	(0.004)		(0.005)	
Health Status at the Beginning				
IADLs only	2.176	**	2.168	**
	(0.185)		(0.188)	
1-2 ADLs	3.401	**	3.392	**
	(0.162)		(0.166)	
3-4 ADLs	5.516	**	5.588	**
	(0.573)		(0.530)	
5-6 ADLs	4.541	**	4.583	**
	(0.926)		(0.706)	
Interaction of Health Status and Utilization				
IADLs only × Inpatient Expenditure	–0.013		–0.013	**
	(0.017)		(0.017)	
1-2 ADLs × Inpatient Expenditure	–0.036	**	–0.035	**
	(0.015)		(0.015)	
3-4 ADLs × Inpatient Expenditure	–0.051		–0.048	**
	(0.041)		(0.039)	
5-6 ADLs × Inpatient Expenditure	–0.106		-1.106	**
	(0.083)		(0.084)	
IADLs only × Physician Service Expenditure	–0.055	**	–0.055	*
	(0.024)		(0.025)	
1-2 ADLs × Physician Service Expenditure	–0.050	**	–0.049	*
	(0.022)		(0.023)	
3-4 ADLs × Physician Service Expenditure	–0.199	**	-0.212	**
	(0.077)		(0.079)	
5-6 ADLs × Physician Service Expenditure	–0.082		–0.092	
	(0.132)		(0.135)	
IADLs only × Prescription Drugs Expenditure	–0.018		–1.018	
	(0.030)		(0.031)	
1-2 ADLs × Prescription Drugs Expenditure	–0.035		–0.035	
	(0.026)		(0.027)	
3-4 ADLs × Prescription Drugs Expenditure	–0.021		–0.020	
	(0.086)		(0.083)	
5-6 ADLs × Prescription Drugs Expenditure	0.011		0.004	
	(0.159)		(0.148)	
Factor loading on permanent heterogeneity, ρ	—		–0.161	
	—		(0.097)	
Factor loading on time-varying heterogeneity, ω	—		–0.224	
	—		(0.111)	

Note: Standard errors are in parentheses.
** indicates joint significance at the 5% level; * 10% level.
Additional explanatory variables include individual demographic information.

Table 5. — Continued

Outcome: 3-4 ADLs	Without Heterogeneity		With Heterogeneity	
Health Care Utilization				
Inpatient Care Expenditure	0.134	**	0.125	**
	(0.024)		(0.024)	
Physician Service Expenditure	0.157	**	0.237	**
	(0.058)		(0.061)	
Prescription Drugs Expenditure	–0.187	**	–0.163	**
	(0.084)		(0.087)	
Square of Prescription Drugs Expenditure	0.053	**	0.051	**
	(0.007)		(0.008)	
Health Status at the Beginning				
IADLs only	3.094	**	3.043	**
	(0.569)		(0.057)	
1-2 ADLs	5.125	**	5.049	**
	(0.472)		(0.467)	
3-4 ADLs	8.903	**	8.899	**
	(0.710)		(0.652)	
5-6 ADLs	8.169	**	–0.163	**
	(0.989)		(0.087)	
Interaction of Health Status and Utilization				
IADLs only × Inpatient Expenditure	–0.037		–0.038	
	(0.031)		(0.031)	
1-2 ADLs × Inpatient Expenditure	–0.086	**	–0.085	**
	(0.025)		(0.025)	
3-4 ADLs × Inpatient Expenditure	–0.118	**	–0.117	**
	(0.045)		(0.042)	
5-6 ADLs × Inpatient Expenditure	–0.241	**	–0.242	**
	(0.083)		(0.083)	
IADLs only × Physician Service Expenditure	–0.085		–0.077	
	(0.071)		(0.070)	
1-2 ADLs × Physician Service Expenditure	–0.129	**	–0.120	*
	(0.060)		(0.060)	
3-4 ADLs × Physician Service Expenditure	–0.294	**	–0.298	**
	(0.093)		(0.095)	
5-6 ADLs × Physician Service Expenditure	–0.108		–0.093	
	(0.139)		(0.142)	
IADLs only × Prescription Drugs Expenditure	–0.046		–0.047	
	(0.081)		(0.082)	
1-2 ADLs × Prescription Drugs Expenditure	–0.062		–0.061	
	(0.067)		(0.067)	
3-4 ADLs × Prescription Drugs Expenditure	–0.044		–0.040	
	(0.103)		(0.100)	
5-6 ADLs × Prescription Drugs Expenditure	0.002		–0.008	**
	(0.163)		(0.153)	
Factor loading on permanent heterogeneity, ρ	—		–0.029	
	—		(0.165)	
Factor loading on time-varying heterogeneity, ω	—		–0.705	
	—		(0.162)	

Note: Standard errors are in parentheses.
** indicates joint significance at the 5% level; * 10% level.
Additional explanatory variables include individual demographic information.

Table 5. — Continued

Outcome: 5-6 ADLs	Without Heterogeneity		With Heterogeneity	
Health Care Utilization				
Inpatient Care Expenditure	0.164	**	0.152	**
	(0.034)		(0.033)	
Physician Service Expenditure	0.179	**	0.327	**
	(0.082)		(0.081)	
Prescription Drugs Expenditure	–0.226	**	–0.196	
	(0.115)		(0.117)	
Square of Prescription Drugs Expenditure	0.049	**	0.051	**
	(0.009)		(0.009)	
Health Status at the Beginning				
IADLs only	1.241		1.455	
	(1.004)		(0.852)	
1-2 ADLs	4.282	**	4.218	**
	(0.692)		(0.620	
3-4 ADLs	7.835	**	7.885	**
	(0.871)		(0.778)	
5-6 ADLs	9.315	**	9.271	**
	(1.062)		(0.815)	
Interaction of Health Status and Utilization				
IADLs only × Inpatient Expenditure	–0.022		–0.016	
	(0.047)		(0.045)	
1-2 ADLs × Inpatient Expenditure	–0.056		–0.054	
	(0.037)		(0.035)	
3-4 ADLs × Inpatient Expenditure	–0.143	**	–0.142	**
	(0.052)		(0.049)	
5-6 ADLs × Inpatient Expenditure	–0.259	**	–0.259	**
	(0.084)		(0.085)	
IADLs only × Physician Service Expenditure	0.290	**	0.258	*
	(0.133)		(0.119)	
1-2 ADLs × Physician Service Expenditure	–0.012		–0.008	
	(0.087)		(0.082)	
3-4 ADLs × Physician Service Expenditure	–0.166		–0.176	
	(0.111)		(0.107)	
5-6 ADLs × Physician Service Expenditure	0.043		0.057	
	(0.147)		(0.146)	
IADLs only × Prescription Drugs Expenditure	–0.207	*	–0.209	
	(0.116)		(0.113)	
1-2 ADLs × Prescription Drugs Expenditure	–0.109		–0.108	
	(0.098)		(0.097)	
3-4 ADLs × Prescription Drugs Expenditure	0.027		0.028	
	(0.126)		(0.123)	
5-6 ADLs × Prescription Drugs Expenditure	–0.036		–0.049	
	(0.171)		(0.159)	
Factor loading on permanent heterogeneity, ρ	—		–0.551	**
	—		(0.209)	
Factor loading on time-varying heterogeneity, ω	—		–1.267	**
	—		(0.250)	

Note: Standard errors are in parentheses.
** indicates joint significance at the 5% level; * 10% level.
Additional explanatory variables include individual demographic information.

Table 5. — Continued

Outcome: Die	Without Heterogeneity		With Heterogeneity	
Health Care Utilization				
Inpatient Care Expenditure	0.248	**	0.332	**
	(0.021)		(0.023)	
Physician Service Expenditure	0.026		0.124	**
	(0.035)		(0.067)	
Prescription Drugs Expenditure	0.161	**	0.407	**
	(0.061)		(0.067)	
Square of Prescription Drugs Expenditure	–0.068	**	–0.115	**
	(0.008)		(0.009)	
Health Status at the Beginning				
IADLs only	1.748	**	1.741	**
	(0.289)		(0.297)	
1-2 ADLs	2.440	**	2.451	**
	(0.260)		(0.267)	
3-4 ADLs	5.667	**	5.543	**
	(0.617)		(0.576)	
5-6 ADLs	6.488	**	6.477	**
	(0.881)		(0.673)	
Interaction of Health Status and Utilization				
IADLs only × Inpatient Expenditure	0.008		0.004	
	(0.027)		(0.029)	
1-2 ADLs × Inpatient Expenditure	0.047		0.044	
	(0.025)		(0.027)	
3-4 ADLs × Inpatient Expenditure	0.015		0.015	
	(0.050)		(0.049)	
5-6 ADLs × Inpatient Expenditure	–0.168		–0.169	**
	(0.082)		(0.083)	
IADLs only × Physician Service Expenditure	–0.029		–0.021	
	(0.046)		(0.049)	
1-2 ADLs × Physician Service Expenditure	–0.079	*	–0.079	
	(0.042)		(0.045)	
3-4 ADLs × Physician Service Expenditure	–0.288	**	–0.298	**
	(0.089)		(0.093)	
5-6 ADLs × Physician Service Expenditure	–0.039		–0.035	**
	(0.131)		(0.135)	
IADLs only × Prescription Drugs Expenditure	0.019		0.017	
	(0.049)		(0.052)	
1-2 ADLs × Prescription Drugs Expenditure	0.017		0.022	
	(0.045)		(0.047)	
3-4 ADLs × Prescription Drugs Expenditure	0.083		0.114	
	(0.096)		(0.094)	
5-6 ADLs × Prescription Drugs Expenditure	0.088		0.088	
	(0.152)		(0.144)	
Factor loading on permanent heterogeneity, ρ	—		1.873	**
	—		(0.157)	
Factor loading on time-varying heterogeneity, ω	—		–0.740	**
	—		(0.187)	

Note: Standard errors are in parentheses.
** indicates joint significance at the 5% level; * 10% level.
Additional explanatory variables include individual demographic information.

Table 6. Distributions of Selected Outcomes: Actual Observation vs. Model Predictions

Year Count	**1st Year**		**2nd Year**		**3rd Year**		**4th Year**		**5th Year**	
Observations from MCBS 1992-1998										
Health Care Expenditures										
Probability of Any Hospitalization	0.21	(0.40)	0.20	(0.40)	0.20	(0.40)	0.21	(0.40)	0.20	(0.40)
Hospital Care Expenditures, If Any	12,794	(14,580)	12,669	(15,690)	12,533	(20,216)	13,580	(18,302)	10,256	(8,614)
Probability of Any Prescription Drugs	0.89	(0.32)	0.89	(0.31)	0.89	(0.30)	0.89	(0.30)	0.90	(0.29)
Prescription Drugs Expenditures, If Any	702	(878)	725	(788)	771	(862)	717	(777)	680	(707)
Physician Services Expenditures	1,656	(3,114)	1,635	(3,270)	1,665	(3,202)	1,440	(2,695)	1,575	(2,281)
Health Outcomes										
No functional disability	0.51	(0.49)	0.51	(0.49)	0.51	(0.49)	0.49	(0.49)	0.48	(0.50)
IADLs only	0.15	(0.36)	0.15	(0.36)	0.16	(0.36)	0.15	(0.36)	0.14	(0.35)
1 or 2 ADLs	0.21	(0.41)	0.20	(0.40)	0.21	(0.40)	0.22	(0.42)	0.21	(0.41)
3 or 4 ADLs	0.07	(0.26)	0.07	(0.25)	0.07	(0.25)	0.08	(0.27)	0.08	(0.27)
5 or 6 ADLs	0.05	(0.21)	0.05	(0.22)	0.07	(0.22)	0.05	(0.22)	0.06	(0.23)
Die	0.05	(0.22)	0.05	(0.21)	0.04	(0.20)	0.05	(0.22)	0.08	(0.28)
Predicted Behavior using Estimated Model										
Health Care Expenditures										
Probability of Any Hospitalization	0.18	(0.39)	0.18	(0.39)	0.20	(0.39)	0.19	(0.40)	0.19	(0.40)
Hospital Care Expenditures, If Any	—*	—*	11,838	(17,650)	12,475	(19,755)	12,211	(19,560)	11,781	(17,518)
Probability of Any Prescription Drugs	0.90	(0.30)	0.92	(0.27)	0.93	(0.26)	0.93	(0.25)	0.93	(0.25)
Prescription Drugs Expenditures, If Any	719	(1,021)	758	(1,034)	788	(1,082)	797	(1,087)	802	(1,079)
Physician Services Expenditures	1,718	(6,337)	1,560	(5,721)	2,168	(10,414)	2,068	(10,595)	1,938	(8,545)
Health Outcomes										
No functional disability	0.50	(0.49)	0.51	(0.49)	0.50	(0.49)	0.50	(0.49)	0.50	(0.50)
IADLs only	0.16	(0.36)	0.15	(0.36)	0.15	(0.36)	0.15	(0.36)	0.15	(0.35)
1 or 2 ADLs	0.19	(0.40)	0.20	(0.40)	0.19	(0.39)	0.19	(0.39)	0.18	(0.39)
3 or 4 ADLs	0.06	(0.25)	0.06	(0.24)	0.06	(0.21)	0.06	(0.24)	0.06	(0.24)
5 or 6 ADLs	0.05	(0.21)	0.04	(0.20)	0.05	(0.21)	0.05	(0.22)	0.05	(0.22)
Die	0.05	(0.22)	0.04	(0.20)	0.05	(0.22)	0.05	(0.22)	0.06	(0.23)

Note: Standard errors are in parentheses. *Indicates not estimated in the empirical model.

Table 7: Immediate and Long-Run Effect of Prescription Drug Coverage
(Comparisons with and without Heterogeneity)

	Without Unobserved Heterogeneity				With Unobserved Heterogeneity			
	Immediate Effect		Long-Run Effect		Immediate Effect		Long-Run Effect	
	No Benefit	With Benefit	No Benefit	With Benefit	No Benefit	With Benefit	No Benefit	With Benefit
Health Care Utilization								
Probability of Prescription Drug Use	0.892	0.906	0.875	0.929	0.905	0.915	0.909	0.934
Prescription Drug Expenditure, If Any	847	895	827	935	636	655	683	831
Probability of Inpatient Care Use	0.198	0.198	0.180	0.196	0.193	0.194	0.178	0.187
Inpatient Care Expenditure, If Any	12956	12956	12,189	14,083	12622	12522	11946	11911
Physician Service Expenditure	1202	1202	1,276	2,670	1566	1563	1676	2159
Health Outcomes								
Survival Rate	0.947	0.951	0.798	0.819	0.947	0.950	0.803	0.822
No I/ADLs	0.487	0.483	0.524	0.494	0.485	0.483	0.519	0.493
IADLs only	0.154	0.155	0.143	0.147	0.154	0.156	0.145	0.149
1-2 ADLs	0.196	0.200	0.173	0.187	0.196	0.199	0.175	0.185
3-4 ADLs	0.068	0.069	0.056	0.066	0.065	0.068	0.057	0.065
5-6 ADLs	0.044	0.044	0.041	0.051	0.043	0.044	0.042	0.051